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## INCORPORATING FLEXIBILITY IN THE DESIGN OF REPAIRABLE SYSTEMS – DESIGN OF MICROGRIDS

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### ABSTRACT

The authors have recently proposed a ‘decision-based’ framework to design and maintain repairable systems. In their approach, a multiobjective optimization problem is solved to identify the best design using multiple short and long-term statistical performance metrics. The design solution considers the initial design, the system maintenance throughout the planning horizon, and the protocol to operate the system. Analysis and optimization of complex systems such as a microgrid is however, computationally intensive. The problem is exacerbated if we must incorporate flexibility in terms of allowing the microgrid architecture and its running protocol to change with time. To reduce the computational effort, this paper proposes an approach that “learns” the working characteristics of the microgrid and quantifies the stochastic processes of the total load and total supply using autoregressive time-series. This allows us to extrapolate the microgrid operation in time and eliminate therefore, the need to perform a full system simulation for the entire long-term planning horizon. The approach can be applied to any repairable system. We show that building in flexibility in the design of repairable systems is computationally feasible and leads to better designs.

### 1. INTRODUCTION

Many times reliable power is needed in remote locations, where either a utility connection is not available or it is unreliable. In contrast to a single power source, microgrids are systems of interconnected sources and loads managed using intelligent power control software (Crawford, 2013). A microgrid is islanded and most likely part of an emergency operation if it is located in an area without a major city utility supply (Skowronska et al., 2013). The military can use islanded microgrids in war zones, where the implications of reliability and cost can be critical.

While many definitions of reliability exist (Kapur and Lamberson, 1977), we consider a microgrid reliable if it supports the loads with minimum service interruptions. This reliability comes however, at a monetary and logistical cost. In this paper, we design a microgrid architecture considering reliability and cost measures by treating it as a repairable system whose operation is characterized using a Minimal Set of Metrics (Pandey et al., 2013). A time-series modeling approach is used to characterize the load and supply random processes (i.e., “learn” their statistical behavior through time) using short-term data and then use them to infer the microgrid operation in the long run. We also incorporate flexibility in design by allowing the microgrid to respond to changes in operating conditions by changing its running protocol and architecture in order to remain optimal throughout its operational time

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(planning horizon). We argue that microgrids provide a representative test-bed in the design and analysis of repairable systems.

For repairable systems (Crow, 1974; Rigdon and Basu, 2000; Wang and Coit, 2005), the classical notion of reliability is not directly applicable. The classical reliability, defined as the probability that the system has not failed before a given time  $t$ , may be misleading because the system may have failed and repaired before time  $t$  (Haldar and Mahadevan, 1999). The classical reliability definition also impedes decision making involving maintenance, availability and service cost of repairable systems. A good maintenance strategy which makes a system available most of the time cannot compensate for too many service interruptions and a potentially high service cost. The tradeoffs between performance, service interruptions and cost are hard to capture. Pandey and Mourelatos (2013) have recently shown that we can systematically approach the design and maintenance of repairable systems using the following three-steps:

1. Identification of the objectives (metrics) for optimal operation as elicited from the decision maker,
2. Modeling of the repairable system over time, including up-time and down-time periods, and
3. Simultaneous optimization of the identified objectives over a pre-specified planning horizon.

In the first step, the decision maker usually identifies pertinent performance requirements which are then converted into mathematical metrics from which a Minimal Set Of Metrics (MSOM) is obtained. A MSOM addresses all system requirements and therefore, captures most of the information about the operational conditions and repairability of the system.

### **Step 1: Metric Identification**

The repairable system in this paper is a remote electric (smart charging) microgrid. The system optimization problem involves multiple conflicting objectives addressing:

1. One or more measures of reliability such as periods of uninterrupted operation or number of failure and repair events,
2. Minimization of capital and running cost, and
3. A measure of longevity; e.g., the planning horizon.

These considerations guide the selection of the MSOM as outlined later in the paper.

### **Step 2: Microgrid Modeling**

The power-load characteristics of a microgrid are managed by turning sources and loads on and off based on how much a load or source is above or below set points. These set points are not known a priori and are usually design variables in the optimization process. Other requirements such as the number of sources and loads as well as the inventory are also considered.

The microgrid simulation over a long time horizon (e.g., one year) may be achieved by either simulating over a short time duration (e.g., hours) and extrapolating over the long time horizon, or by using a coarse time scale over the long time horizon. Unless done properly, what is learned in a short simulation time may not be applicable to the entire planning horizon. If a coarse time scale is used to cover a long planning horizon, many transient effects can be missed since they happen within seconds. Transient effects may for example, include the imbalance caused when generators and invertors react differently to a change in load conditions. A simulation using large time steps may miss these effects. On the other hand, using a fine time scale is computationally prohibitive for long simulations.

Another major challenge in simulating complex repairable systems, and in particular microgrids, is the effect of uncertainty. Unless models with a fine time scale are used over long periods of time, we cannot obtain reliable information about the system. For example, we may encounter a chance failure and assume that the microgrid is unreliable or alternatively by luck, we may not see any failure in a short period even if the microgrid is unreliable. To properly capture the effect of uncertainty, multiple replications of the system response are required to estimate the statistics of performance metrics. This increases the computational effort even more.

### **Step 3: Multiobjective Optimization**

A mathematical optimization over the discussed attributes is generally set up as a non-linear mixed integer problem because of the non-linear objective functions and the combination of discrete and continuous decision variables (Whitefoot et al., 2011). In our work we use a multiobjective genetic algorithm (GA).

#### **1.1 Flexible design and our approach**

Our discussion so far indicates that the optimal design of a microgrid is computationally challenging. The need to analyze microgrids accurately and in detail stems from the need for flexible operation. A flexible microgrid responds to changes in operating conditions by changing its running protocol and architecture in order to remain optimal throughout the operational time

period. In essence, a flexible microgrid avoids a single point design, an approach used in stochastic optimization, where a “robust design” with the highest “expected utility” is chosen (de Neufville and Scholtes, 2011). Flexibility allows the system to change itself accommodating uncertain events and increasing therefore, its reliability.

To address the time scale and length of analysis issues, we propose using time-series modeling to “learn” the characteristics of the load and supply random processes from a short operation, and extrapolate thereafter to a longer period. The running protocol of a microgrid influences its need to service a total load by supplying a total power. The “learning” we propose, characterizes the load random process and determines the characteristics of the supply random process in response to the load. This ensures that the relative levels of load and supply and their correlation in time are captured. Once the load and supply processes are quantified, we can use them to estimate long term reliability metrics. This approach is theoretically sound as opposed to extrapolating the results of a short simulation run. As we have mentioned, short simulations are prone to missing extreme events and therefore, relative frequency of failure events are likely to be miscalculated. Modeling the statistics of the entire process eliminates this issue.

A repairable system must be designed over multiple metrics that capture different facets of the system performance. We will show how to calculate the metrics of the system using a quantified random process approach. Our method can be used to also assess new concepts such as “gridable” vehicles. When vehicle systems link into a microgrid in order to share power sources and loads, a vehicle-to-grid (V2G) system is formed (Kempton and Tomic, 2005). The analysis and design of such microgrids is complicated and a method to extrapolate what is learned in a short time period can be very useful.

The paper is organized as follows. Section 2 describes our methodology including the chosen minimal set of metrics and the time-series modeling of the load and supply stochastic process. Section 3 provides details on the design and operation of a smart charging microgrid including results and a sensitivity analysis. Finally, Section 4 concludes and discusses future research directions.

## 2. METHODOLOGY

### 2.1 Metric-based design of repairable systems

The classical reliability theory of repairable systems uses metrics such as the Mean Time Between Failures (MTBF) and availability to characterize the performance

of a repairable system (Haldar and Mahadevan, 1999). These metrics are calculated using times between failures and system repair frequency and durations. However, they only capture one statistic of the time to failure. The MTBF captures the mean, while the availability is simply the ratio of system up-time to the total duration the system is in operation. A system that has a skewed distribution of the time between failures will not have its performance well represented by the MTBF or availability.

To account for these limitations, we have proposed using a Minimal Set of Metrics (MSOM) to fully describe the performance of repairable systems (Pandey and Mourelatos, 2013). The MSOM should be defined so that the metrics, individually or collectively, cover most aspects of the system performance. The reader is referred to (Pandey and Mourelatos, 2013) for more details.

For the microgrid example of this paper, we use the metrics of cost ( $C$ ), minimum failure free period with 80% probability ( $T_{0.8}$ ), and number of failures ( $N_f$ ) within the planning horizon. In the optimization phase, a Pareto front is generated over these metrics, which are then traded off by the decision maker to obtain the optimal combination that best satisfies his/her preferences.

### 2.2 Microgrid operation

Microgrids consist of many interconnected loads and sources and include intelligent power management to enable a robust and reliable operation with substantial fuel and maintenance economies over their service life. Most microgrids have an AC module and a DC module. The AC module connects and disconnects different sources and loads and handles the AC power. The DC module manages the DC sources (e.g., batteries and solar arrays), and inverts them to get AC power which is then supplied to the AC module.

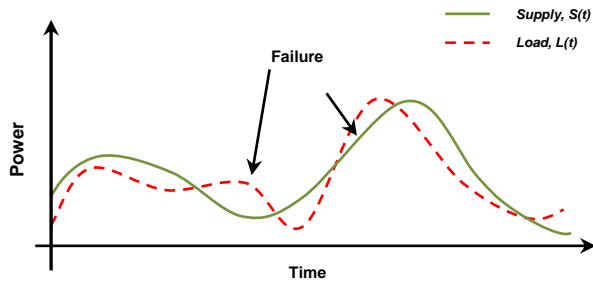
Common power sources in a microgrid include a utility main if available, generators, solar arrays, wind turbines and rechargeable vehicles. The sources are given priority numbers to determine the reverse order in which they will be taken offline, if necessary. A low number indicates that the source is critical and will be taken offline after the other sources have already been taken offline. The microgrid load is also explicitly modeled. The sources and loads are shed and added depending on the system’s excess capacity. Common loads include buildings, battery charging, and other miscellaneous loads. Each load has also a priority number.

At each time, the running protocol of the microgrid decides, based on load requirements, how many sources to keep on, what capacity to run them at, and how much excess capacity to have in order to account for stochastic load variations. If we characterize the load random process and therefore, know its behavior through time,

we can account for sudden load changes by suitably increasing or decreasing the supply. However, because of inherent uncertainty in load and partial system failures, this is not always possible.

Failures are due to inadequate capacity to service the load and/or to actual subsystem failures. Failures are expected because cost considerations usually preclude a microgrid from never failing. For a dynamic microgrid system, it is very difficult to predict its performance in the long term without simulating the grid for a long duration. Considering that most electrical transients happen in milliseconds, we must run simulations with a very short time step for months at a time in order to fully account for them. This is of course computationally impractical.

We propose to “learn” the characteristics of the load profile  $L(t)$  and the resulting supply profile  $S(t)$ , as enacted by an intelligent power management protocol. It is necessary to not only characterize the random processes  $L(t)$  and  $S(t)$  but also the correlation between them. This is because a supply that is not well correlated with load will either lead to failures, waste of power because of overproduction when not needed, or both. A short period of a few days can be used for the “learning” process. Based on the quantified stochastic behavior, we can then extrapolate the two random processes for a long time (several months or even years) and record the number of failures where the supply is less than the load (Fig. 1) and the times failure occurred. This information can be used to quantify the system performance metrics.



**Figure 1.** Realizations of the supply and load random processes

### 2.3 Time series modeling of load and supply

We use time series modeling to characterize the load and supply random processes. Time series models have been extensively used to characterize random processes (Ruppert, 2004; Nikolaidis et al., 2011). They combine Auto-Regressive (AR) models, Integrated (I) models, and a Moving Average (MA) model. The Integrated (I) model is used if the process is non-stationary. All models use a feedback mechanism based on either past observations, past standard errors (MA), or a

combination of the two to determine future observations. AR models are the most commonly used. They use a weighted average of past observations in addition to a white noise error term, to capture the correlation at times  $t_1$  and  $t_2$  where  $\tau = t_2 - t_1$  is small.

Consider a random process  $X(t)$ . A sample function  $x(t)$  is discretized in the time interval  $[0, T]$  using a uniform time step  $\Delta t$  so that  $x_i = x(t_i)$  and  $t_i = (i-1) \cdot \Delta t$ . For the AR( $p$ ) model, the discretized sample function is represented as

$$x_i - \mu = \phi_1(x_{i-1} - \mu) + \phi_2(x_{i-2} - \mu) + \dots + \phi_p(x_{i-p} - \mu) + \varepsilon_i \quad (1a)$$

where  $\mu$  is the temporal mean of the process,  $\varepsilon_i \equiv N(0, \sigma_e^2)$  is Gaussian white noise and  $\phi_1, \phi_2, \dots, \phi_p$ , are feedback parameters to be estimated. The parameter  $p$  indicates the order of the autoregressive process which in turn, indicates the level of correlation to past observations.

Eq. (1a) can be used to create a derivative process as

$$y_i = \mu_i + L(x_i) \quad (1b)$$

where  $\mu_i$  is mean of the process  $Y(t)$  at time  $i$ ,  $x_i$  is a zero mean process modeled using the AR model of Eq. (1a), and  $L$  is a function of  $x_i$ . To preserve stationarity and ergodicity of  $x_i$ ,  $L$  must be linear and  $\mu_i$  constant.

After the feedback parameters are estimated in Eq. (1a), a residual series  $E(t) = X(t) - \hat{X}(t)$  is formed as the difference between the actual  $X(t)$  and the estimated  $\hat{X}(t)$  processes and statistical tests are performed to make sure the random variables  $E_t$  and  $E_{t+\tau}$  are uncorrelated for every  $\tau$ . Details are provided in (Ruppert, 2004).

### 3. A SMART CHARGING MICROGRID EXAMPLE

As discussed in Section 2, the microgrid implements control by sensing power usage at various loads and routing power to and from several components to bring the system to the desired state of operation. This entails switching contactors on or off. When initiated, the grid starts at the system equilibrium and remains in this state unless/until the excess system capacity moves outside specified set-points. Excess capacity is defined as the

available power in excess of the current load. The microgrid is assumed failed if it cannot meet the load requirements; i.e., the instantaneous supply  $S(t)$  is less than the instantaneous load  $L(t)$ . There are various scenarios where this can happen such as the total capacity is not enough to meet an unexpected spike in load, one or more sources or contactors have failed, a software error in implementing the control has occurred, or any combination of the above. If a failure occurs, we either repair the failed component(s) or wait for the microgrid to recover if the supply capacity is reached (soft failure).

One way to obtain the optimal architecture of a microgrid (Pandey et al., 2013), is by solving the multiobjective optimization problem of Eq. (2). For that, we use the Non-dominated Sorting Genetic Algorithm – II (NSGA-II) (Deb et al., 2002). The three objectives of cost ( $C$ ), minimum failure free period with 80% probability ( $T_{0.8}$ ), and number of failures ( $N_f$ ) within the planning horizon are considered. The design variables are the set-points where the loads and sources are taken offline/online, and the number of sources (generators, solar arrays and contactors) we start with.

$$\text{Min}_{\mathbf{x}} \{-T_{0.8}, N_f, C\} \quad (2)$$

where:

$$\mathbf{x} = \{s_{ls}, s_{so}, s_{lo}, s_{ss}, n_{gen}, n_{solar}, n_{contacts}\}^T$$

$$T_{0.8} = F_{T_{working}}^{-1}(0.2)$$

$$C = C_{initial} + C_{repair}$$

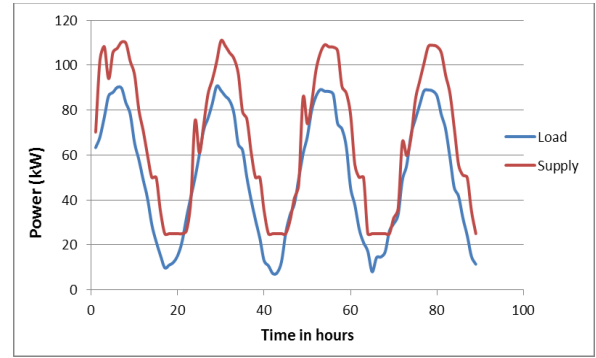
subject to:

$$g(\mathbf{x}): P = 8760$$

$$n_{gen}, n_{solar}, n_{contacts}, n_{batt} \in N$$

$$s_{ls}, s_{so}, s_{lo}, s_{ss} \in [0, 100]$$

The simulation is run for 8760 hours (1 year) using a coarse time scale for each value of the design variable vector. One of the solutions, shown in Table 1, from the generated Pareto front is chosen for further analysis. Fig. 2 shows the source and load behavior for about 90 hours of operation for the solution in Table 1. At certain time instances the load is higher than the supply because of the stochasticity in the load and/or component failures. This is expected because no system can be fully reliable.



**Figure 2.** Realizations of load and supply processes for the optimal solution in Table 1

**Table 1.** One of the Pareto front solutions

Decision variables	Value
$s_{ls}$	0.6%
$s_{so}$	18%
$s_{lo}$	11%
$s_{ss}$	22%
$n_{gen}$	6
$n_{contacts}$	17
Attributes	
$T_{0.8}$	563 hrs
$N_f$	6
$C$	\$1.08M

Simulating the microgrid operation through time, even for specified values of the design variables, requires a substantial computational effort because for each time step we must obtain details of the microgrid operational state such as sensing the load, turning sources and loads off/on and repairing/replacing components as needed. To address this issue, we propose that the microgrid be simulated for only a short period of time (much shorter than the one year planning horizon) and use the simulated results to characterize the supply and load processes. This is possible only if the stochastic part of the processes after subtracting the trend is stationary. In other words, we propose to use short time data to “learn” the statistical characteristics of the process for the entire planning horizon. Subsequently, realizations of the characterized processes can be used to calculate the attributes in Eq. (2) without carrying out simulations.

To demonstrate our approach, we assume that the microgrid load is a derivative process as in Eq. (1b). The

random part is represented by the zero-mean, fourth-order, AR model of Eq. (3) where time  $t$  is measured in hours.

$$L(t_i) = 50 + 40 \sin\left(\frac{2\pi}{24}\right) + 20(0.034\epsilon_{i-1} + 0.155\epsilon_{i-2} + 0.206\epsilon_{i-3} + 0.258\epsilon_{i-4} + 0.344\epsilon_i) \quad (3)$$

The random process of Eq. (3) captures pertinent aspects of loads encountered in real life. The process has a trend with a stable element of 50 kW, and a sinusoidal element with period of a day and a 40 kW amplitude. The latter simulates diurnal load changes. The stochastic part has four feedback parameters and a white noise term represented by the standard normal random variable  $\epsilon_i$ . The standard deviation of the white noise at each time step is  $20 \times 0.3448 = 6.89$  kW. In reality, the time series model is determined from actual load realizations observed over a short period of time.

Since the supply is a function of load, we model it using the same fourth-order AR model of Eq. (3) with two changes. First, the white noise in the supply is correlated with the white noise in the load and second, there is an excess capacity built-in to ensure that the supply is in general, greater than the load. In principle, a process representing the time varying difference between the load and supply may be used. It is preferable however, to model the load and supply processes separately because we have no control over the load and the supply is controlled by the running protocol of the microgrid.

Two strategies are considered for implementing the excess capacity. In the first strategy, we multiply the deterministic part of the load by a factor of  $(1 + \phi)$ , and in the second strategy we add a fixed additional power to the modeled load. Eqs (4) and (5) express the two strategies.

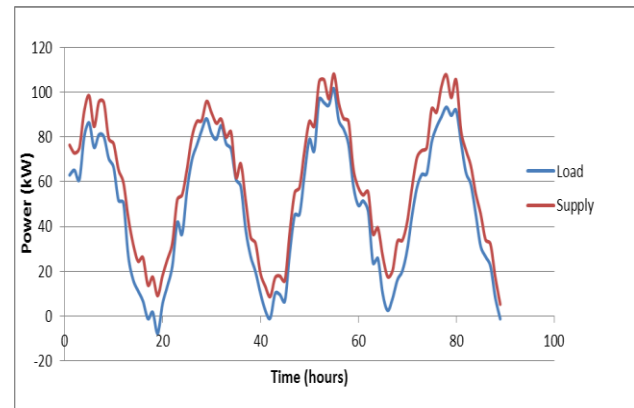
$$S(t_i) = (1 + \phi) \left( 50 + 40 \sin\left(\frac{2\pi}{24}\right) \right) + 20(0.034\omega_{i-1} + 0.155\omega_{i-2} + 0.206\omega_{i-3} + 0.258\omega_{i-4} + 0.344\omega_i) \quad (4)$$

$$S(t_i) = \delta + 50 + 40 \sin\left(\frac{2\pi}{24}\right) + 20(0.034\omega_{i-1} + 0.155\omega_{i-2} + 0.206\omega_{i-3} + 0.258\omega_{i-4} + 0.344\omega_i) \quad (5)$$

The correlation between  $\epsilon_i$  and  $\omega_i$  is denoted by  $\rho_{\epsilon\omega}$  which is less than one. The higher its value, the better the microgrid control algorithm “knows” the value of the load including the uncertain component of it. A

value of 1 implies that the load stochasticity is perfectly modeled by the algorithm and thus, a supply value to meet the load can be theoretically created with no excess capacity. In this case, the microgrid will never fail unless some of its components fail.

We vary the value of  $\rho_{\epsilon\omega}$  to investigate its effect on the microgrid performance metrics. Fig. 3 shows one realization of the load and supply processes according to Eqs (3) and (4) for  $\rho_{\epsilon\omega} = 0.9$  and  $\delta = 11$ . We note that the supply is generally higher than the load, except for some infrequent chance failures because of the load stochasticity.



**Figure 3.** Realizations of simulated load and supply processes for Strategy 2

We now evaluate different working scenarios of the microgrid which is optimized over the three long term metrics of cost, MFFP and number of failures. Strategy 1 uses a percentage of the supply as excess supply and Strategy 2 generates a fixed additional (excess) power over the assessed load. To compare the two strategies, we use the cost of excess capacity  $C_e$ . In our opinion, the cost of operation is best measured by the cost of excess capacity the microgrid generates over time. This is expected to be less than the cost of setting up or running the microgrid. Because it is imperative to meet the required loads, the cost to do so cannot be considered a good performance metric. A microgrid can be expensive if it must meet higher load requirements, and cannot be called worse than a microgrid that is cheaper only because the load requirements are low. The best microgrid therefore, is the one that best allocates the excess power to minimize failures.

For this example, the cost to generate power is 10 cents per kWh. The number of failures  $N_f$  is the number of distinct times the microgrid fails during the planning horizon of one year. Recall that the proposed method can be used to analyze a grid for many years with a very small additional computational effort. The third metric of MFFP,  $T_{0.8}$ , is calculated using the running durations of



the grid between failures. It is simply the 20<sup>th</sup> percentile of the running durations.

### 3.1 Sensitivity analyses

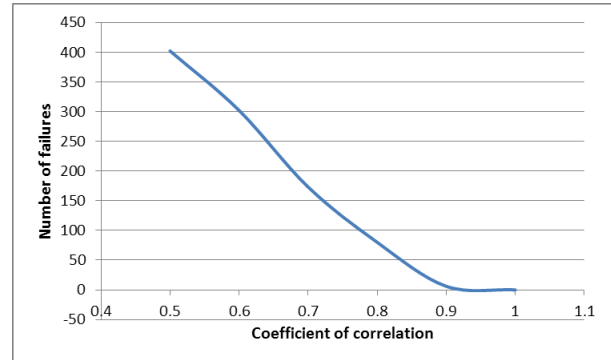
Sensitivity analyses are presented here for different model parameters and optimal solutions for Strategy 2. We show that Strategy 2 provides a better way to build-in excess capacity.

We first compare the two strategies to build excess capacity according to Eqs (4) and (5). Realizations of the microgrid load and supply random processes are generated for 8760 hours. For comparison purposes, we calculated the values of  $\phi$  and  $\delta$  in Eqs (4) and (5) that result in the same number of failures (equal to 6) during the planning horizon. The solution of Table 1 generates 135,002.4 kWh of excess energy, costing \$13,500.24 (135,002.4 kWh times 10 cents per kWh) in insurance against chance failures. Fixing the number of failures at 6, Strategy 1 generates 329,963.71 kWh of excess energy over the course of the year for a \$32,996.37 cost of insurance against chance failures. In contrast, Strategy 2 with an excess power of 11 kW generates only 96,091.27 kWh of extra energy for only a cost of \$9,609.12. Strategy 2 is therefore, the most cost effective and we use it for further analysis.

The takeaway is that building extra supply capacity as a percentage of the load is wasteful because when the load is high, there is less likelihood of it increasing substantially any more while the opposite is true when the load is low. Therefore, we should build extra capacity in terms of fixed power in kW and not as a percentage of the load.

Next we study the sensitivity of the number of failures and of the cost with respect to the correlation coefficient  $\rho_{\varepsilon\omega}$  between the load and supply noise terms (Eqs 3 and 5). Fig. 4 shows the expected decrease in the number of failures. The failures fall to zero when the supply is perfectly correlated with the load. While this seems intuitive, there are two things to notice. First, accurate modeling of the load, and a microgrid response with a supply that meets that load quickly, are essential for a reliable microgrid. The shorter the delay in the response, the better the correlation between load and supply would be. Second, the cost does not change much with the value of the correlation coefficient. This is because when the supply is equal to the sum of the expected load and a fixed load  $\delta$ , we can directly calculate the surplus generation (and hence cost) over a year by multiplying the number of hours a microgrid is operational by  $\delta$ . This number is not affected much by the actual value of the load if the stochastic element is small compared to the mean (see Eq. 3). The change in cost due to error in assessing the load because of a low value of  $\rho_{\varepsilon\omega}$  will also average out over time and the

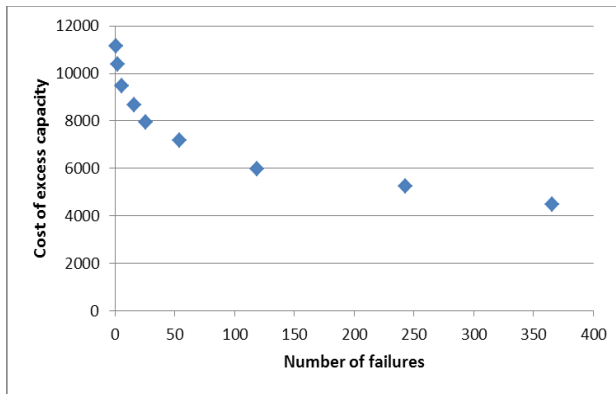
overall cost of excess capacity will remain relatively constant.



**Figure 4.** Effect of increasing correlation between load and sources on number of failures

We now concentrate on the optimal solution using Strategy 2. We will determine the optimal extra power (excess capacity)  $\delta$  in Eq. (5). Since the problem involves multiple attributes we expect to get multiple non-dominated solutions. Fig. 5 shows the Pareto front over the two attributes of cost and number of failures. The decision maker can use it to choose the most desirable combination of attributes based on his/her preferences. The optimal  $\delta$  depends on the selected cost and the number of failures from the Pareto front.

Recall that there are three attributes. For simplicity, the attribute of MFFP is not shown. If the decision maker selects the design with an approximate cost of \$8,842 and 20 failures, the solution is to select Strategy 2 to provide excess supply and use a value of 10 kW for  $\delta$ . The corresponding MFFP value will be 139.6 hours. Of course, this is contingent on  $\rho_{\varepsilon\omega}$  being equal to 0.9. While quantifying the load and source processes, we must ensure that they and the correlation between them are modeled correctly. The proper choice of supply as a function of time, including the optimal excess capacity, depends on how accurately the load is modeled.



**Figure 5.** Tradeoff between cost from excess capacity and number of failures for Strategy 2

Our results show that we can characterize the load and supply random processes using short duration simulations (i.e., “learn” the operational characteristics of the microgrid) and use them to predict the stochastic behavior of load and supply for long duration simulations. In this case, further analysis of operating scenarios, including the optimal strategy of adding excess capacity, is possible with limited computational effort.

For sudden changes of the load profile, the corresponding supply profile can be established relatively easily. However to obtain the microgrid architecture in response to these changes, which may entail adding or removing generators or electric vehicles, will require more sophisticated models. One approach is to build a Kriging model (Sacks et al., 1989) between the microgrid architecture and the optimal supply profile. A truly flexible design can then be realized where rapidly changing needs are met quickly and optimally with minimal computational effort.

#### 4. CONCLUSIONS AND FUTURE WORK

Repairable systems are hard to analyze because many classical reliability engineering concepts do not apply readily. Microgrids are repairable systems that can be excellent test-beds in research, design and analysis of repairable systems. Remote systems have become more electrified over time and their power needs and generation capabilities have increased. Their optimal operation is therefore, critical. A microgrid as a collection of power sources for a specialized use must be reliable (meeting its intended purpose under uncertainty most of the time) over a long time period at a reasonable cost. Available optimization methods using long-duration simulations may not be practical because of high computational effort. We must simulate the microgrid operation for a long period of time in order to properly quantify the time-dependent load and the required supply as implemented by the chosen protocol.

Many simulations are necessary to obtain the optimal microgrid design that provides the right trade-off between different performance metrics under uncertainty. Because the simulations are computationally expensive, many shortcuts are used in the literature such as using a coarse time scale ignoring therefore transients, or running the simulation for a short time to the detriment of properly estimating long term performance metrics.

This paper addressed this important issue using a different approach. We proposed to quantify the load and supply random processes using actual load and supply data over a short time and establish the correlation between the two processes. The quantified processes are then used to generate load and supply realizations over the long planning horizon and calculate performance metrics of interest such as cost, number of failures and MFFP. Because actual simulations are performed over a short time, or for a limited number of designs, the computational cost is minimal. We showed that this is a feasible strategy to optimize microgrids over various metrics and also perform sensitivity analysis on various model assumptions.

Using our method, we made two recommendations on how to design a microgrid. First, we should model the load stochastic process as accurately as possible, thereby increasing the chance that supply will be higher than the load most of the time during the time of interest. Second, an optimal supply of power can be obtained by adding a fixed and optimally determined amount of power, to the value of the stochastic load at any time instead of a percentage of the load. Not only does it lead to higher reliability but it also makes the calculation of running cost easier.

In future work, we will quantify the load and supply random processes to include discrete chance events of failure of components or intentional shutting off of a load or a source. Furthermore, we will reduce the computational effort using time-dependent metamodels between the microgrid architecture and its long-term operation including measures of reliability and operational cost.

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#### REFERENCES

1. Crawford, M., 2013, “Microgrids May Power Entire U.S. in Future”, <https://www.asme.org/engineering->

- topics/articles/renewable-energy/microgrids-may-power-entire-future Date accessed, 24th Jan 2013.
2. Crow, L. H., 1974, *Reliability Analysis for Complex, Repairable Systems in Reliability and Biometry*, eds F. Proschan & R.J. Serfing, SIAM, 379-410, Philadelphia.
  3. De Neufville and Scholtes, S., 2011, *Flexibility in Engineering Design*, MIT Press, Cambridge MA, p. 17.
  4. Deb, K., Pratap, A., Agrawal, S. and Meyarivan, T., 2002, "A Fast Elitist Non-dominated Sorting Genetic Algorithm for Multi-objective Optimization: NSGA-II," *IEEE Transactions on Evolutionary Computation*, 6(2), 182–197.
  5. Haldar, A. and Mahadevan, 1999, *Probability Reliability and Statistical Methods in Engineering Design*, 1st Edition, John Wiley and Sons.
  6. Kapur, K. C. and Lamberson, L. R., 1977, *Reliability in Engineering Design*, 1<sup>st</sup> Edition, John Wiley and Sons.
  7. Kempton, W. and Tomic, J., 2005, "Vehicle-to-grid Fundamentals: Calculating Capacity and Net Revenue," *Journal of Power Sources*, 144(1), 268-279.
  8. Nikolaidis, E., Mourelatos, Z. P. and Pandey, V., 2011, *Design Decisions under Uncertainty with Limited Information*, 1<sup>st</sup> Edition, Taylor and Francis.
  9. Skowronska, A., Gorsich, D., Pandey, V., Mourelatos, Z. P., Mange, J. and Dunn, A., 2013, "Global Strategies for Optimizing the Reliability and Performance of a US Army Mobile Power Transfer System," *Proceedings of the 2013 Ground Vehicle Systems Engineering and Technology Symposium (GVSETS)*, Troy, MI.
  10. Pandey, V., Skowronska, A. G., Mourelatos, Z. P., Gorsich, D. and Castanier, M., 2013, "Reliability and Functionality of Repairable Systems using a Minimal Set of Metrics: Design and Maintenance of a Smart Charging Microgrid," *ASME International Design Engineering Technical Conferences*, Paper DETC2013-12376, Portland, OR.
  11. Pandey, V. and Mourelatos, Z. P., 2013, "New Metrics to Assess Reliability and Functionality of Repairable Systems," *SAE International Journal of Materials and Manufacturing*, 6(3), 402-410.
  12. Rigdon, S. and Basu, A., 2000, *Statistical Methods for the Reliability of Repairable Systems*, 1<sup>st</sup> Edition, Wiley-Interscience, pp. 224.
  13. Ruppert, D., *Statistics in Finance*, Springer Texts, 2004.
  14. Sacks, J., Welch, W. J., Mitchell, J. J., and Wynn, H. P., 1989, "Design and Analysis of Computer Experiments," *Statistical Science*, 4(4), 409-435.
  15. Wang, P. and Coit, D. W., 2005, "Repairable Systems Reliability Trend Tests and Evaluation" *Proceedings of the Annual Reliability and Maintainability Symposium*, 416 – 421.
  16. Whitefoot, J., Mechtenberg, A. R., Peters, D. L. and Papalambros, P. Y., 2011, "Optimal Component Sizing and Forward-looking Dispatch of an Electrical Microgrid for Energy Storage Planning," *Proceedings of the ASME 2011 International Design Engineering Technical Conferences*, Washington, DC.